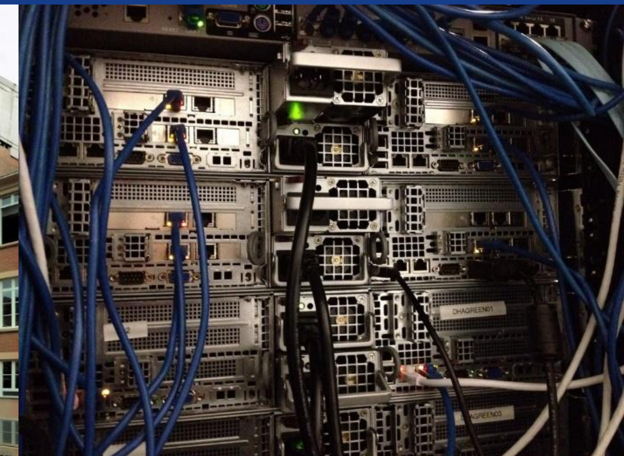

General patient representation from Electronic Health Records

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MACHINE LEARNING
POWER TO THE DATA
Meetup

February 14, 2018

Massachusetts Institute of Technology

srlf SOCIÉTÉ DE RÉANIMATION DE LANGUE FRANÇAISE

UNIVERSITÉ PARIS DESCARTES

ASSISTANCE PUBLIQUE HÔPITAUX DE PARIS
www.aphp.fr

Context

More than 160 participants, 20 teams...

https://www.aphp.fr/contenu/datathon-dat-icu-intensive-care-unit-4-projets-innovants-selectionnes-lissue-de-48h-danalyse

Massachusetts Institute of Technology

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More context

Autorisation par la Commission Nationale Informatique et Libertés de la constitution d’un entrepôt de données de santé à l’AP-HP

Publié le 09/03/2017. Page vue 1422 fois. | Communiqués de presse

L’autorisation de la CNIL ouvre l’accès aux recherches sur données dépassant le cadre de l’équipe de soins

Dans sa délibération du 19 janvier 2017, la Commission Nationale Informatique et Libertés (CNIL) a autorisé l’Assistance Publique – Hôpitaux de Paris à mettre en œuvre un traitement automatisé de données à caractère personnel ayant pour finalité la constitution de l’entrepôt de données de santé (EDS).

LES COORDONNÉES DU SERVICE PRESSE

CONTACTER LE SERVICE DE PRESSE DE L'AP-HP

https://www.aphp.fr/contenu/autorisation-par-la-commission-nationale-informatique-et-libertes-de-la-constitution-dun

MIMIC dataset

MIMIC is an openly available dataset developed by the MIT Lab for Computational Physiology, comprising deidentified health data associated with ~40,000 critical care patients. It includes demographics, vital signs, laboratory tests, medications, and more.

https://mimic.physionet.org/

Motivation

- Secondary use of **electronic health records (EHRs)** promises to advance **clinical research** and **precision medicine**:
  - diseases prediction algorithms
  - personalized prescriptions & treatment recommendations
  - patient similarity & clinical trial recruitment

- The success of these applications **depends on feature selection and data representation**:
  - A **domain expert** designate the patterns to look for in the EHR
    - *albuminuria is an important factor in Chronic kidney disease*
  - A **clinical informatician** determines codes and terminologies
    - *type 2 diabetes mellitus [hbA1C > 7.0, 250.00 ICD-9 diagnosis code, mention in the clinical notes]*

List of ICD-9 codes

From Wikipedia, the free encyclopedia

The following is a list of codes for International Statistical Classification of Diseases and Related Health Problems[1] [2].

- List of ICD-9 codes 001–139: infectious and parasitic diseases
- List of ICD-9 codes 140–239: neoplasms
- List of ICD-9 codes 240–279: endocrine, nutritional and metabolic diseases, and immunity disorders
- List of ICD-9 codes 280–289: diseases of the blood and blood-forming organs
- List of ICD-9 codes 290–319: mental disorders
- List of ICD-9 codes 320–389: diseases of the nervous system and sense organs
- List of ICD-9 codes 390–459: diseases of the circulatory system
- List of ICD-9 codes 460–519: diseases of the respiratory system
- List of ICD-9 codes 520–579: diseases of the digestive system
- List of ICD-9 codes 580–629: diseases of the genitourinary system
- List of ICD-9 codes 630–679: complications of pregnancy, childbirth, and the puerperium
- List of ICD-9 codes 680–709: diseases of the skin and subcutaneous tissue
- List of ICD-9 codes 710–739: diseases of the musculoskeletal system and connective tissue
- List of ICD-9 codes 740–759: congenital anomalies
- List of ICD-9 codes 760–779: certain conditions originating in the perinatal period
- List of ICD-9 codes 780–799: symptoms, signs, and ill-defined conditions
- List of ICD-9 codes 800–999: injury and poisoning
- List of ICD-9 codes E and V codes: external causes of injury and supplemental classification

ICD-9-CM **Section I**

General Coding Guidelines

- Use both the Alphabetic Index and the Tabular List when locating and assigning a code.
- Locate each term in the Alphabetic Index and verify the code selected in the Tabular List.
- For example, code for the condition "combined hyperlipidemia"

Hyperlipidemia **272.4**
carbohydrate-induced **272.1**
combined **272.2**

272.2 Mixed hyperlipidemia
Broad- or floating-betalipoproteinemia
Combined hyperlipidemia

ICD-9 diagnosis code

HEALTH INSURANCE CLAIM FORM

CARRIER

14. DATE OF CURRENT ILLNESS, INJURY, or PREGNANCY (LMP) MM DD YY QUAL.
15. OTHER DATE QUAL. MM DD YY
16. DATES PATIENT UNABLE TO WORK IN CURRENT OCCUPATION FROM MM DD YY TO MM DD YY
17. NAME OF REFERRING PROVIDER OR OTHER SOURCE
17a.
17b. NPI
18. HOSPITALIZATION DATES RELATED TO CURRENT SERVICES FROM MM DD YY TO MM DD YY
19. ADDITIONAL CLAIM INFORMATION (Designated by NUCC)
20. OUTSIDE LAB? YES NO $ CHARGES
21. DIAGNOSIS OR NATURE OF ILLNESS OR INJURY Relate A-L to service line below (24E) ICD Ind.

A. B. C. D.

E. F. G. H.

I. J. K. L.

22. RESUBMISSION CODE ORIGINAL REF. NO.
23. PRIOR AUTHORIZATION NUMBER

24. A. DATE(S) OF SERVICE From MM DD YY To MM DD YY	B. PLACE OF SERVICE	C. EMG	D. PROCEDURES, SERVICES, OR SUPPLIES (Explain Unusual Circumstances) CPT/HCPCS MODIFIER	E. DIAGNOSIS POINTER	F. $ CHARGES	G. DAYS OR UNITS	H. EPSDT Family Plan	I. ID. QUAL.	J. RENDERING PROVIDER ID. #
1								NPI	
2								NPI	
3								NPI	
4								NPI	
5								NPI	
6								NPI	

25. FEDERAL TAX I.D. NUMBER SSN EIN
26. PATIENT'S ACCOUNT NO.
27. ACCEPT ASSIGNMENT? (For govt. claims, see back) YES NO
28. TOTAL CHARGE $
29. AMOUNT PAID $
30. Rsvd for NUCC Use
31. SIGNATURE OF PHYSICIAN OR SUPPLIER INCLUDING DEGREES OR CREDENTIALS (I certify that the statements on the reverse apply to this bill and are made a part thereof.)

SIGNED DATE

32. SERVICE FACILITY LOCATION INFORMATION

a. NPI b.

33. BILLING PROVIDER INFO & PH # ( )

a. NPI b.

PHYSICIAN OR SUPPLIER INFORMATION

NUCC Instruction Manual available at: www.nucc.org

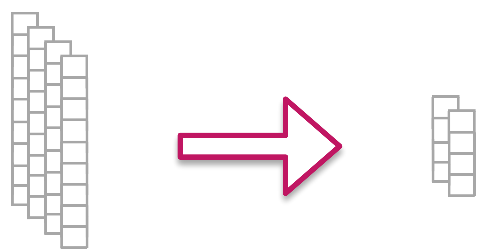
PLEASE PRINT OR TYPE

APPROVED OMB-0938-1197 FORM 1500 (02-12)

SAMPLE

Objectives

<u>**Goal**</u>: **reduce the dimensionality** by building a **generalist embedding** for each stay with **deep learning** methods, **spanning the whole semantic spectrum of healthcare data**



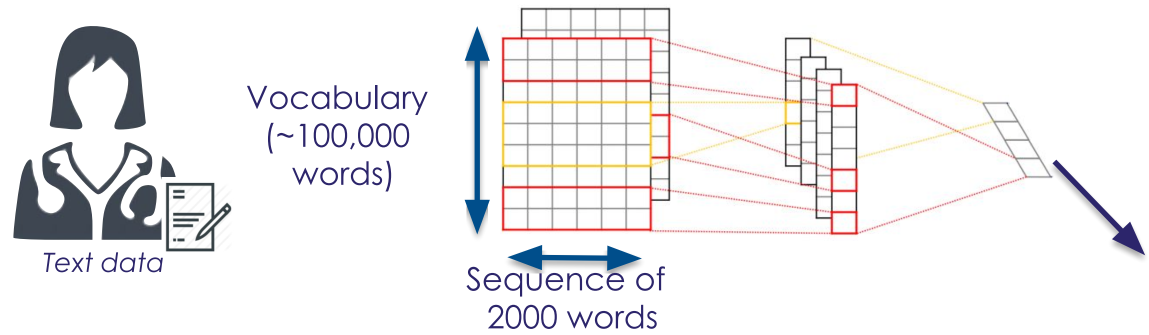
raw data

embedding space
similar patient should be near

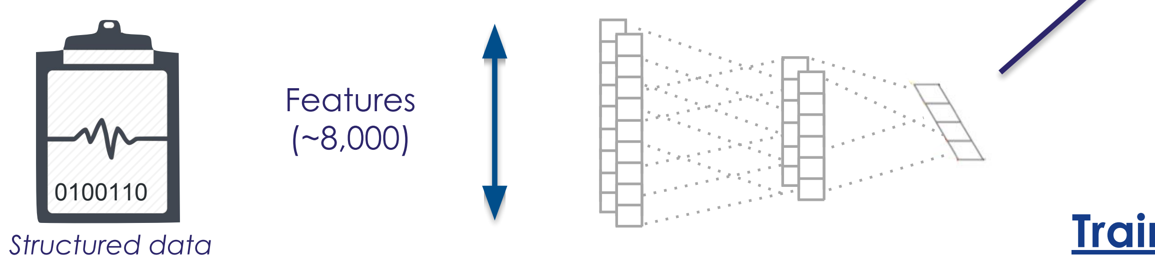
Methods: deep learning architecture

Our idea: **two models** for each type of data **trained jointly** to get one embedding representation of patient stays

- **Convolutional Neural Network**



- **Multi Layer Perceptron**

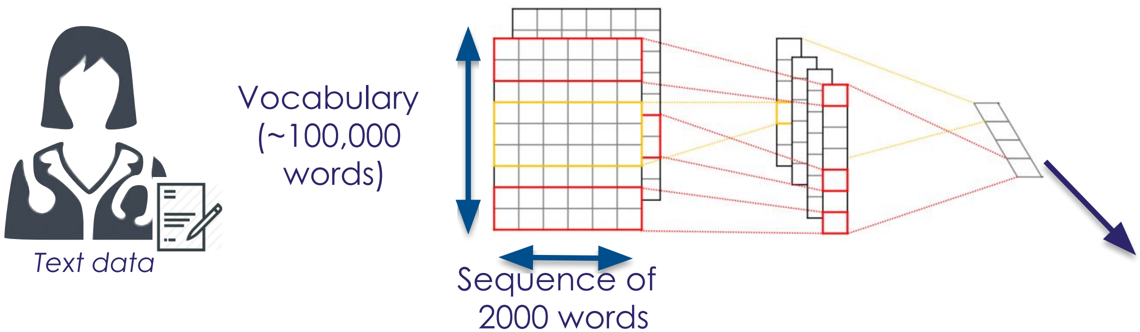


__Training__
- Mini batch SGD
- few hours on 1 GPU

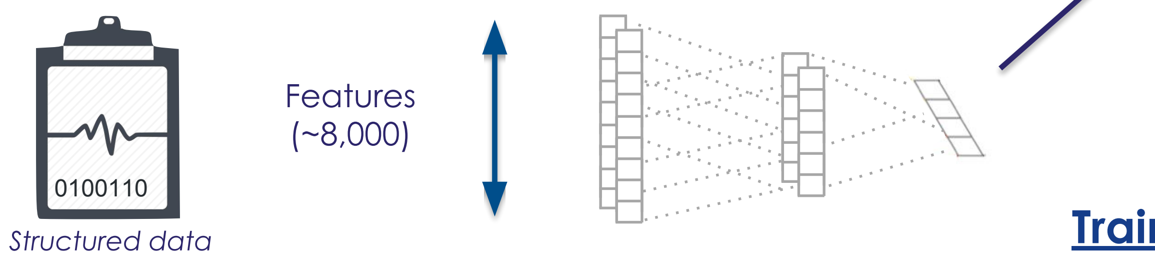
Methods: deep learning architecture

Our idea: **two models** for each type of data **trained jointly** to get one embedding representation of patient stays

- **Convolutional Neural Network**



- **Multi Layer Perceptron**



<u>**Training**</u>

- Mini batch SGD
- few hours on 1 GPU

Results - Diagnosis code assignment

- level 1 : **19 chapters**
  - neoplasms, infectious and parasitic

Baseline Random Forests
PPV: 0.706, Sensitivity: 0.433, F1: 0.537

PPV: 0.861, Sentivity: 0.782, F1: 0.820

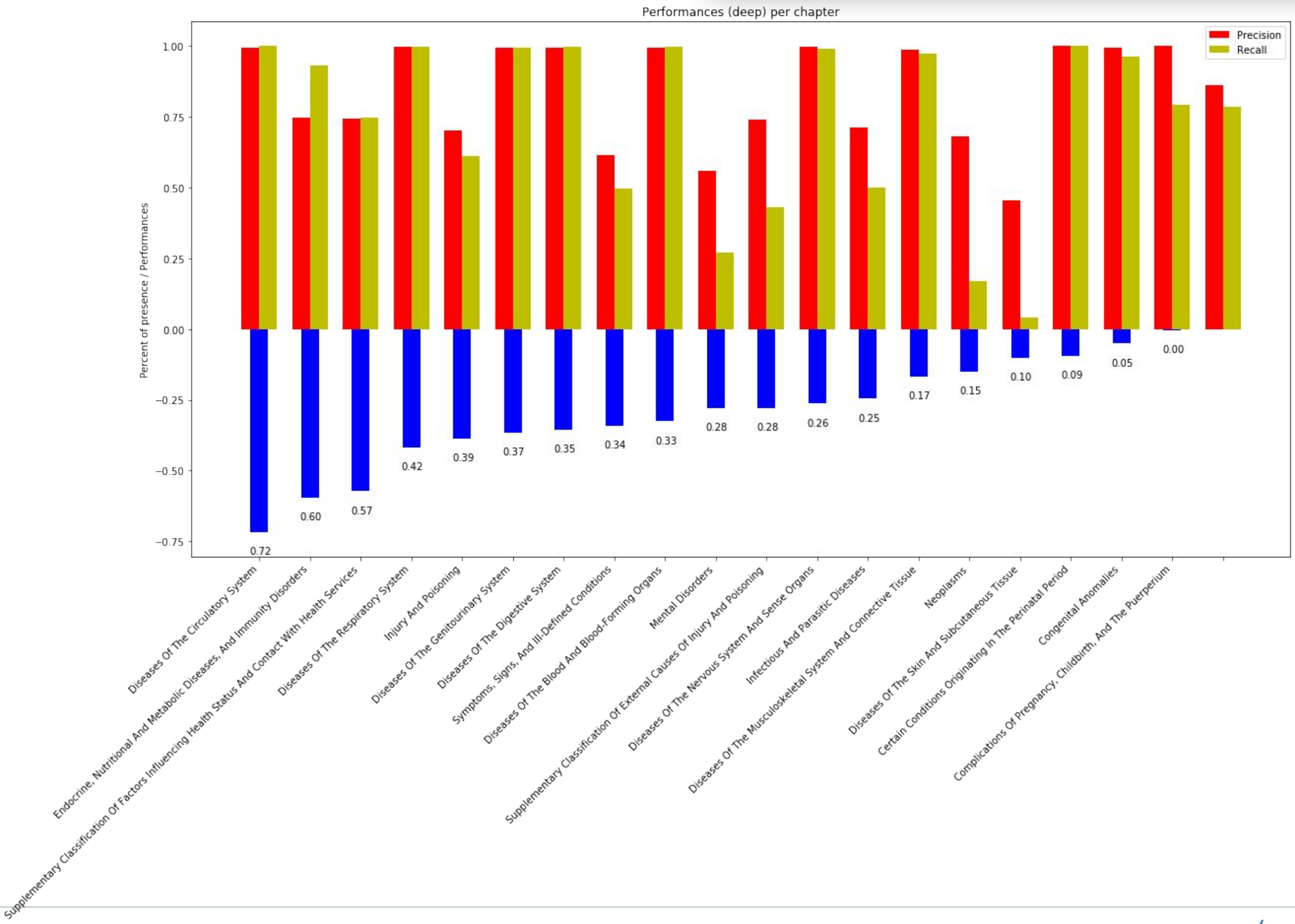
- level 2 : **146 sub-chapters**
  - digestive neoplasms, neuroendocrine tumors
  - mycoses, venerial diseases

PPV: 0.740, Sensitivity: 0.462, F1: 0.570

Appendix: ICD-9 Classification

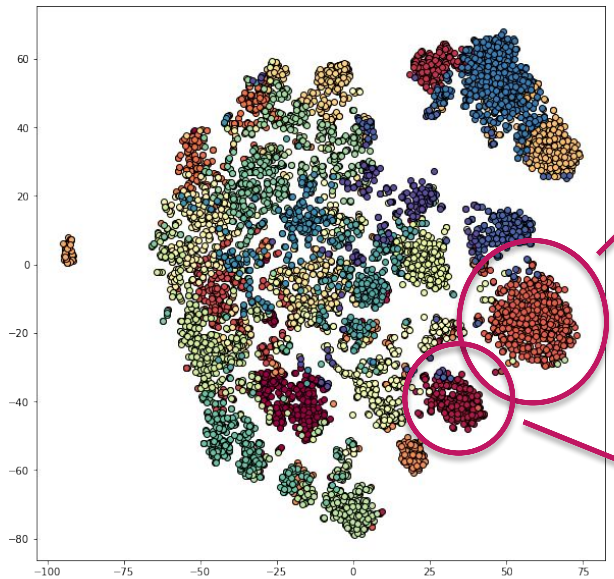
ICD-9 Classification: **chapters**

Precision: 0.861, Recall: 0.782, F1: 0.820



Patient stay similarity

Unsupervised clustering method (k means)



New borns
Almost all stays in cluster contain code « Certain Conditions Originating In The Perinatal Period »

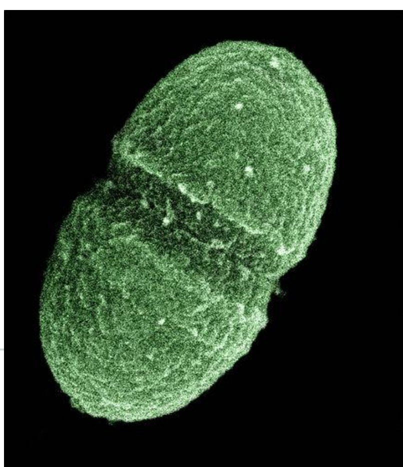
ARDS
Almost all stays in cluster contain code « Acute Respiratory Distress Syndrom »

Results - Medical concept encoded in the embedding

RESISTANT
ENTEROCOCCUS

v1

ENTEROCOCCUS



Results - Medical concept encoded in the embedding

RESISTANT
ENTEROCOCCUS

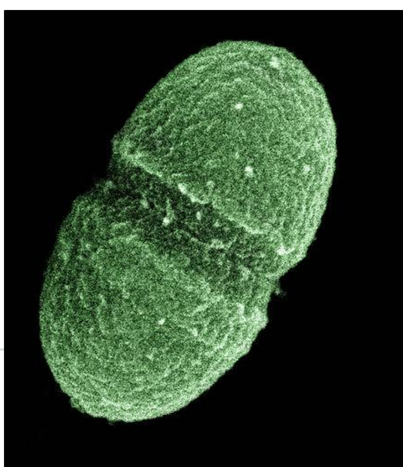
RESISTANT
STAPH AUREUS COAG
POS

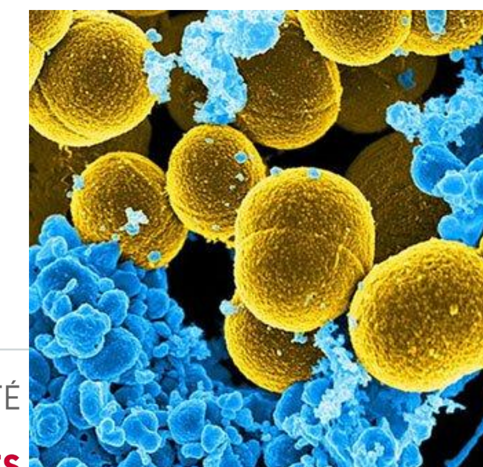
v1

v2

ENTEROCOCCUS

STAPH AUREUS COAG
POS





Results - Medical concept encoded in the embedding

RESISTANT
ENTEROCOCCUS

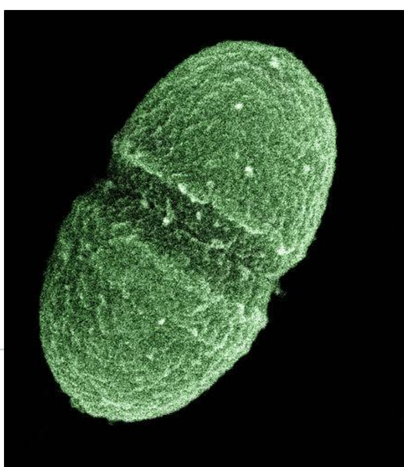
RESISTANT
STAPH AUREUS COAG
POS

v1

v2

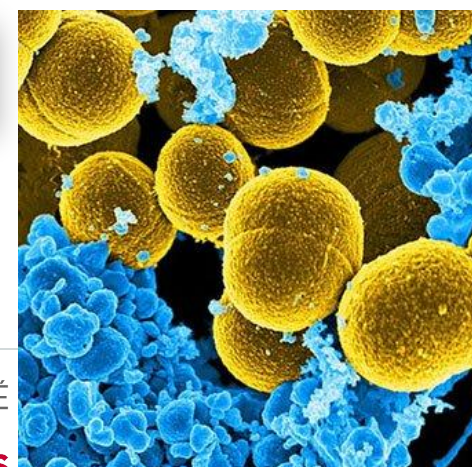
ENTEROCOCCUS

STAPH AUREUS COAG
POS

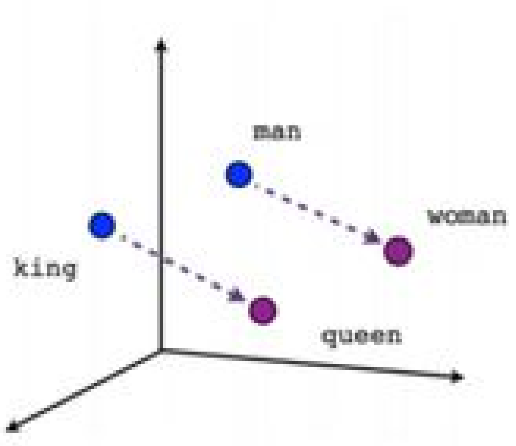


$\boxed{\cos(v1, v2) \sim 0.394}$

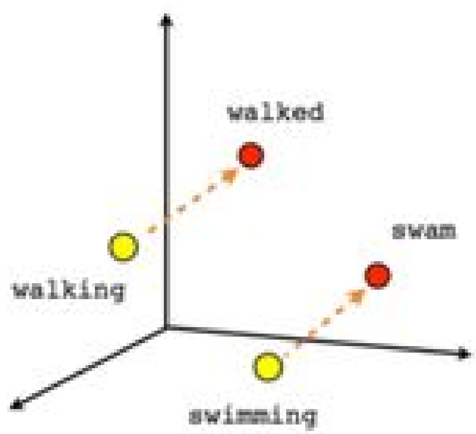
>> 0.04



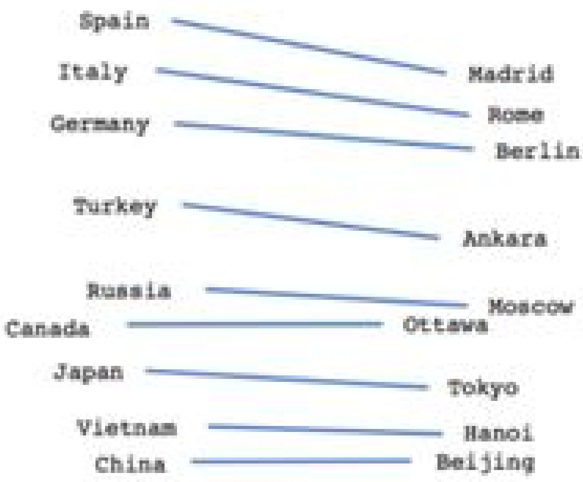
Results - Medical concept encoded in the embedding



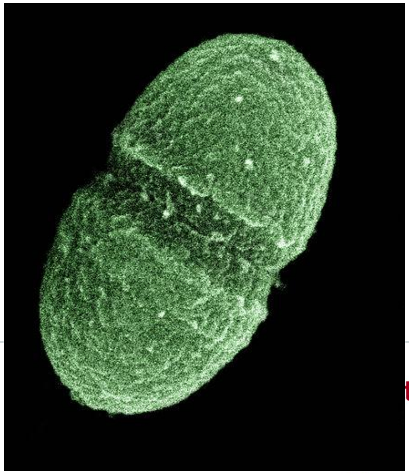
Male-Female



Verb tense

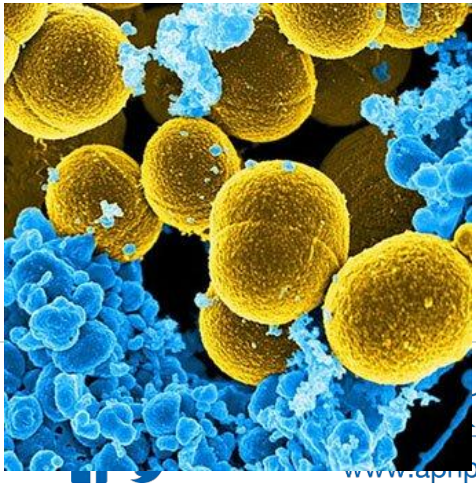


Country-Capital



cos(v1, v2) ~ 0.394

>> 0.04



Results - Medical concept encoded in the embedding

RESISTANT
E. COLI

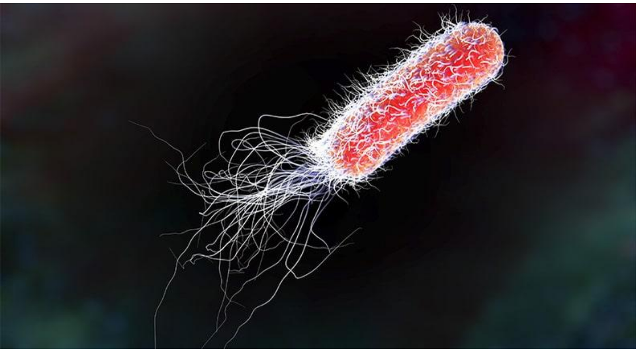
v1

RESISTANT
P. AERUGINOSA

v2

E. COLI

P. AERUGINOSA



cos(v1, v2) ~ 0.706

Discussion

Results:

- **Generalist clinical fingerprint** giving promising results on similarity-based **stay clustering**
- Encouraging metrics on **ICD-9 classification** proves validity of the architecture
- Learnt representation correctly **encodes medical semantics** such as antibiotic resistance

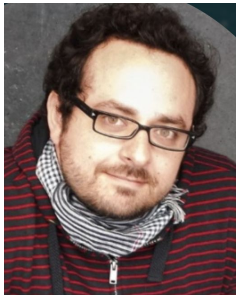
Limits:

- **Not enough data** (54k stays) to fully benefit from Deep Learning
  -> 216k stays analyzed by Google, UCSF, Stanford, UCM (2018)
- Temporality dimension aggregated to 1 data point per stay

Perspectives and applications:

- **Deep Learning** works better with more data
  APHP database (millions of stays)
- **Cohort selection** for clinical studies
- A compact representation **available for any predictive model**

Team



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Methods: data extraction

MIMIC III database : EHR data from **54,000 ICU stays**

Text data from medical reports

- *vocabulary size of* ***119,000 words***

- 2M clinical notes
- first 2000 words per stay

Structured medical data:

- medical procedures, drugs, in/out fluids, microbiology, transfers, demographics,
- SNOMED CT concept extractions from text (exact match)

- numerical or categorical (one hot encoded)

- features selection *:* ***44,000 ->*** *8,000 most discriminant (lowest p-values chi square)*